Radiation variability in regional climate: the cases of tropical and Arctic interannual variations

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Outline

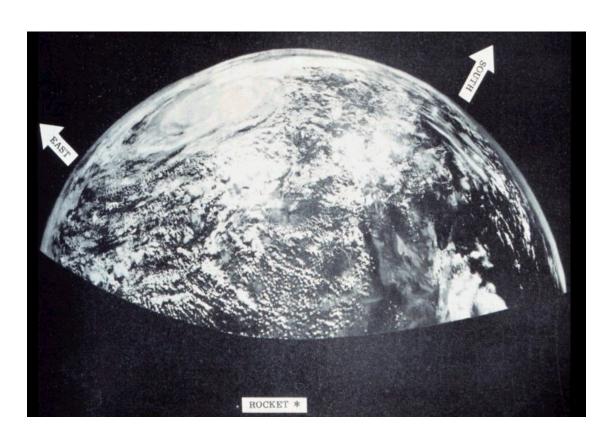
- Some motivating questions
 - Radiation closure at higher order
 - Different budgets
- Method
 - A (new) set of Kernels for TOA/SFC/ATM radiation
- Case of ENSO
 - Importance to get cloud radiative sensitivity right
- Case of Arctic Sea Ice
 - (non)Linearity issue and a proposed NN model for feedback analysis

Use of radiation data

 Monitoring/characterizing weather & climate



First meteor. satellite (Explorer 7: Oct 13, 1959): an Earth radiation budget instrument

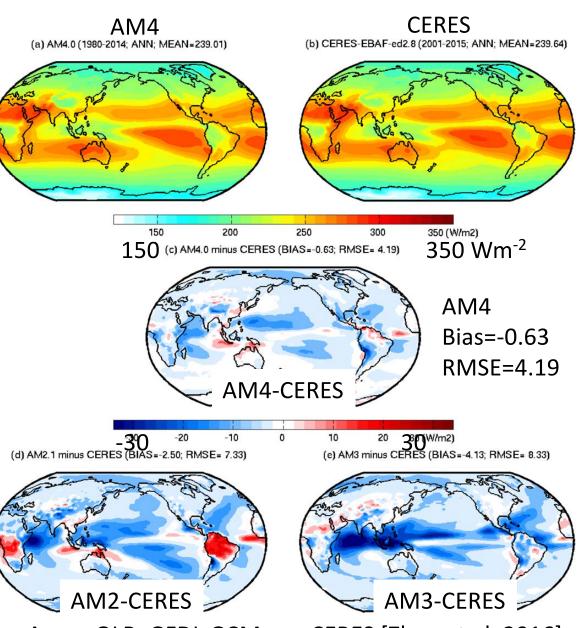


Pre-satellite era: Rocket view of the Earth

Use of radiation data

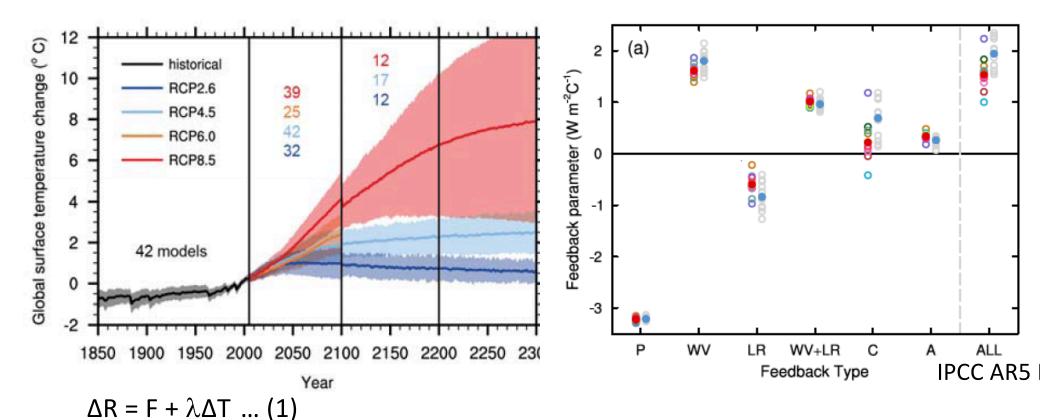
- Monitoring/characterizing weather & climate
- Validating models (theories)
 - Average Radiation (R):GCM GM Bias < 1 Wm⁻²
 - Variation of R (Δ R) : Spatial/temporal bias ~10 Wm⁻²

=> Next objective: Radiation closure of ΔR



Annu. OLR, GFDL GCMs vs. CERES [Zhao et al. 2016]

Forcing + Feedback => Climate Change



T: surface temperature; R: net radiation; F: radiative forcing

 λ : Sensitivity (feedback) parameter = $\lambda_{Planck} + \lambda_{water\ vapor} + \lambda_{lapse-rate} + \lambda_{cloud} + \lambda_{albedo} + ...$

$$\lambda_X = \Delta R_X / \Delta T \text{ [W m}^{-2} \text{ K}^{-1}]$$

A popular kernel method for measuring ΔR_X

Non-cloud: $\Delta R_X = K_X \cdot \Delta X$, $K_X = \frac{\partial R}{\partial X}$

Cloud: $\Delta R_C = \Delta R - \sum \Delta R_X$

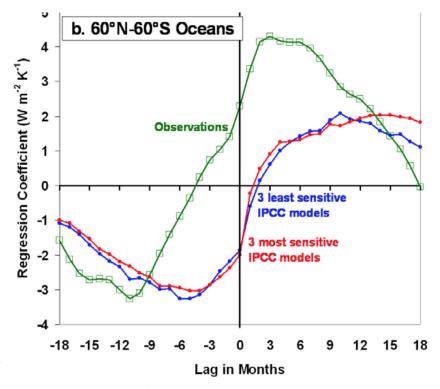
To validate climate feedback (λ) it is essential to get ΔR_X right, i.e., to achieve radiation closure with ΔR !

Need to keep ΔR(GCM) checked

- Is GCM cloud feedback too positive?
 - Obs-model (CERES vs CMIP3) comparisons suggest too positive radiative feedback in GCMs. [Spencer&Braswell 2011].
 - Exchanges between Lindzen&Choi 2009, 2011,
 Spencer&Braswell 2011; Murphy 2010,
 Trenberth 2010, Dessler 2011; Trenberth 2011,

•••

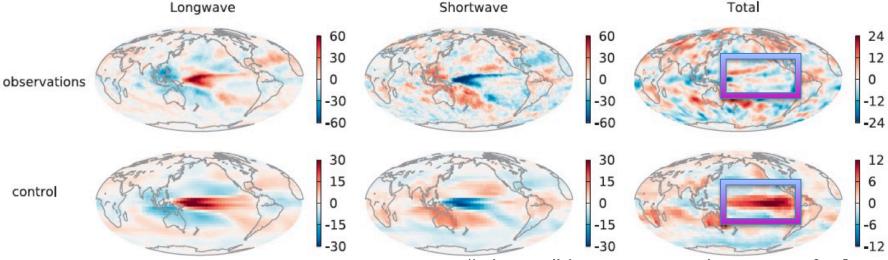
• Updates : New GCMs, longer CERES record, different budgets, ...



R-T lead/lag regression [S&B2011]

R: CERES (upward positive);

T: HadCRUT3



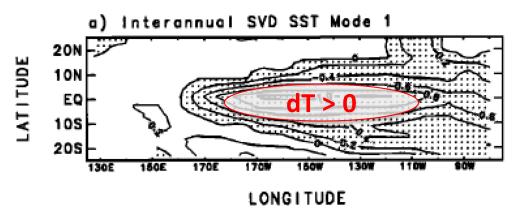
"Glaring" bias in central-east Pacific [Dessler 2013]

Importance of different budgets: regional

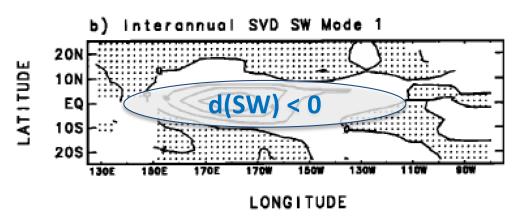
- In Tropics, noted in earlier studies is a strong negative SW feedback at surface in central Pacific during ENSO. Remaining questions:
 - ATM budget and linkage to Bjerknes feedback?
- In Arctic, direct drive of sea ice variability is surface (as opposed to TOA) radiation.
 - Cloud vs. albedo?

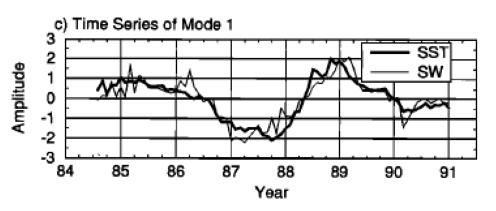
Need to analyze ΔR with respect to SFC and ATM budgets.

SST, ISCCP SW [Waliser et al. 1994]



Sign definition: Rad. flux is downward positive.





A SET OF KERNELS FOR ANALYZING ΔR_X AT TOA AS WELL AS SFC AND ATM

Radiative kernels

• Computation of K_X

$$K_X = \frac{\partial R}{\partial X} \approx [R(X + \Delta X) - R(X)]/\Delta X$$

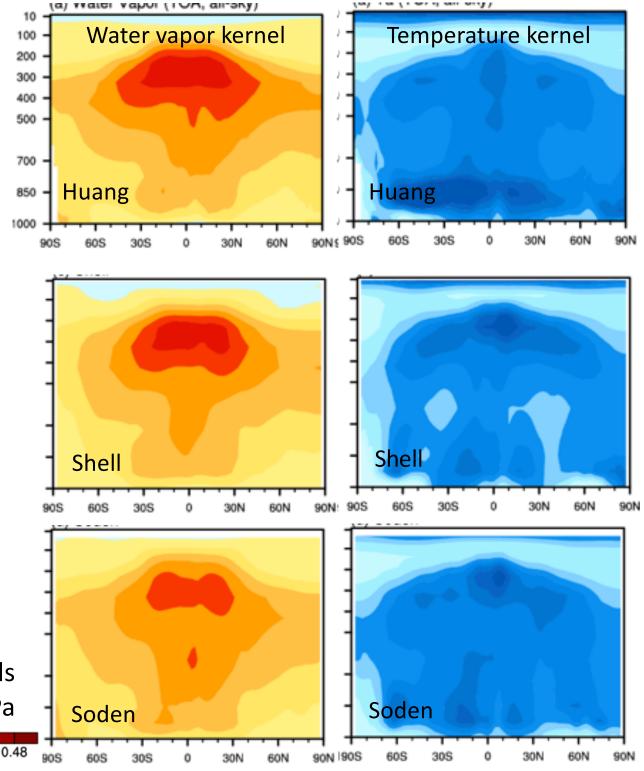
R(X): RRTM

X: ERAi

Global 2.5°x2.5°, 5 years' 6-hourly atmos profiles used to compute K_X , and then averaged at each grid point for every calendar month. [Huang et al. 2017 JGR]

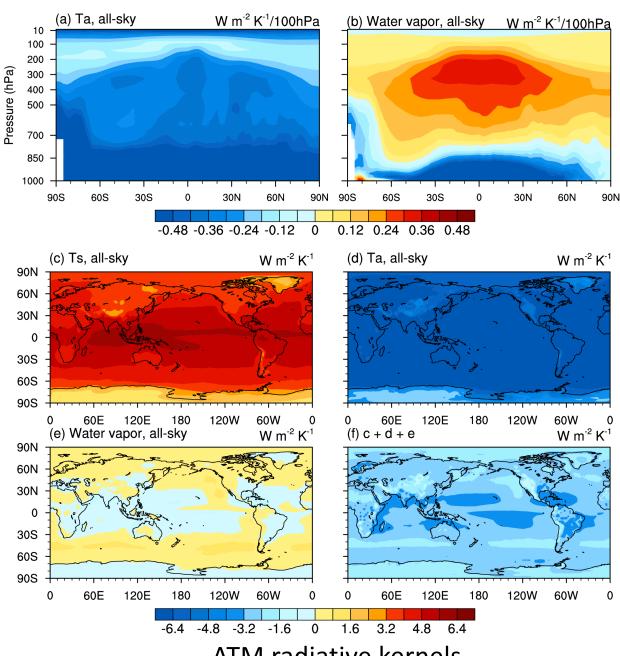
 TOA kernels in agreement with other kernel sets

> TOA radiative kernels Units: W m⁻² K⁻¹ / 100 hPa



Atmospheric radiation kernel

- R_{atm}=R_{toa}-R_{sfc}: positive downward (warming)
- a, b) **Zonal and annual mean** atmospheric temperature and water vapor kernel.
- c, d, e) Annual mean surface temperature, <u>vertically</u> <u>integrated</u> atmospheric temperature and water vapor kernels.
- f) The <u>sum</u> of c-e: atmospheric radiation change when the surface and atmosphere uniformly warm by 1K while conserving relative humidity.



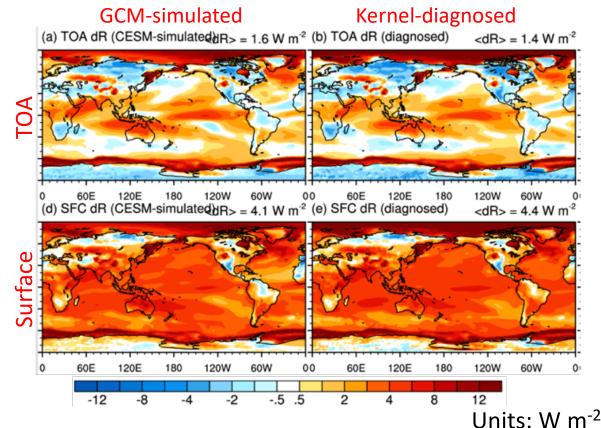
ATM radiative kernels Units: W m⁻² K⁻¹ / 100 hPa

Validation – Radiation Closure Test

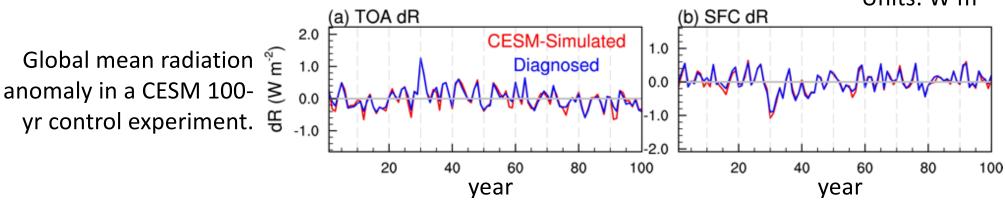
Radiation closure test:
 comparison between GCM simulated clear-sky radiation
 anomaly and that
 reproduced by the kernels:

$$\Delta R_{total}$$
 $\geq \sum K_X \Delta X$

- Test 1: global warming
- Test 2: unforced internal variability



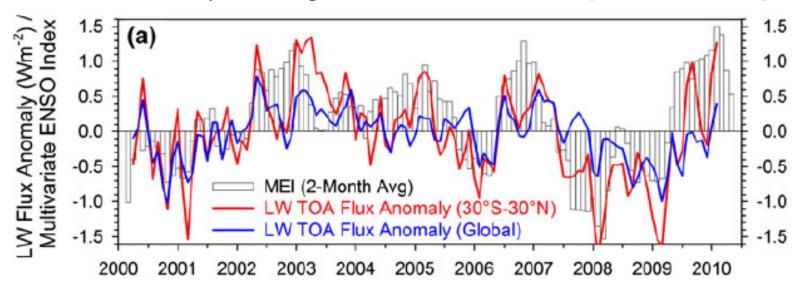
Radiation anomaly in a CESM 2xCO2 experiment

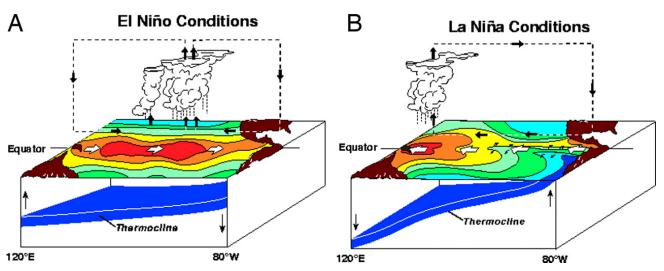


ENSO

Radiation anomaly associated with ENSO

ENSO drives tropical and global radiation anomalies [Loeb et al. 2012]

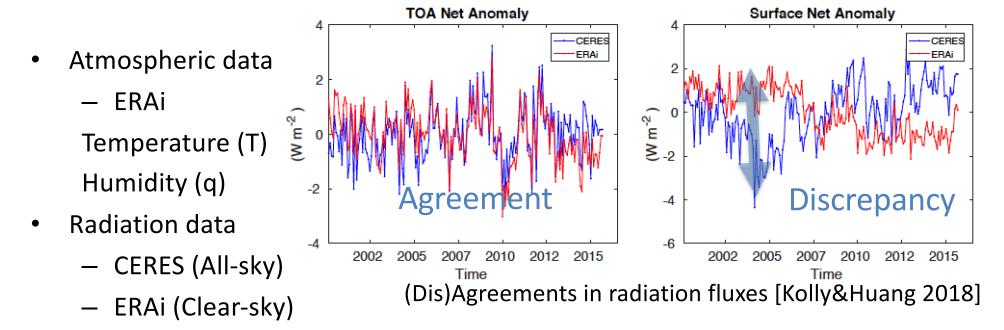




• Questions:

- Respective radiative feedbacks $\Delta R_X / \Delta T$?
- Link to dynamics(Bjerknes) feedback
 - How do GCMs do?

Method and data



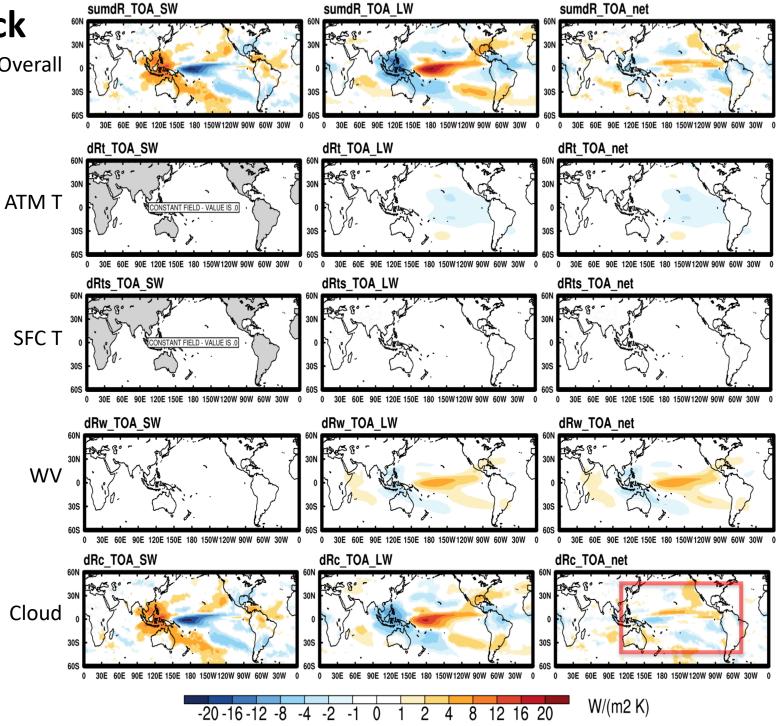
- Radiation budget decomposition: kernel method
 - $\Delta R_X = K_X \cdot \Delta X$ for non-cloud feedbacks, adjusted CRF [Shell et al. 2008] for ΔR_{cloud}
 - ERAi atmosphere-based kernels [Huang et al. 2017]
- "Feedback"
 - $-\lambda_X=regr(\Delta R_X,SST)$: monthly rad anomaly regressed to Nino3.4 SST units: W m⁻² K⁻¹

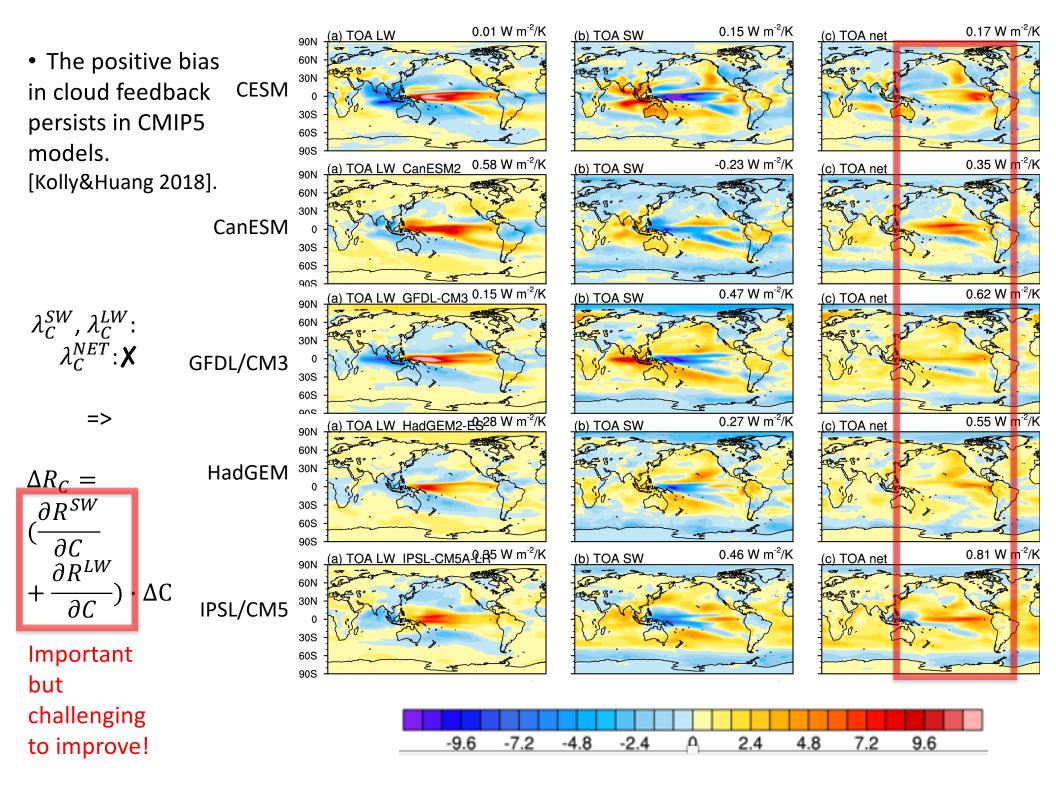
TOA feedback

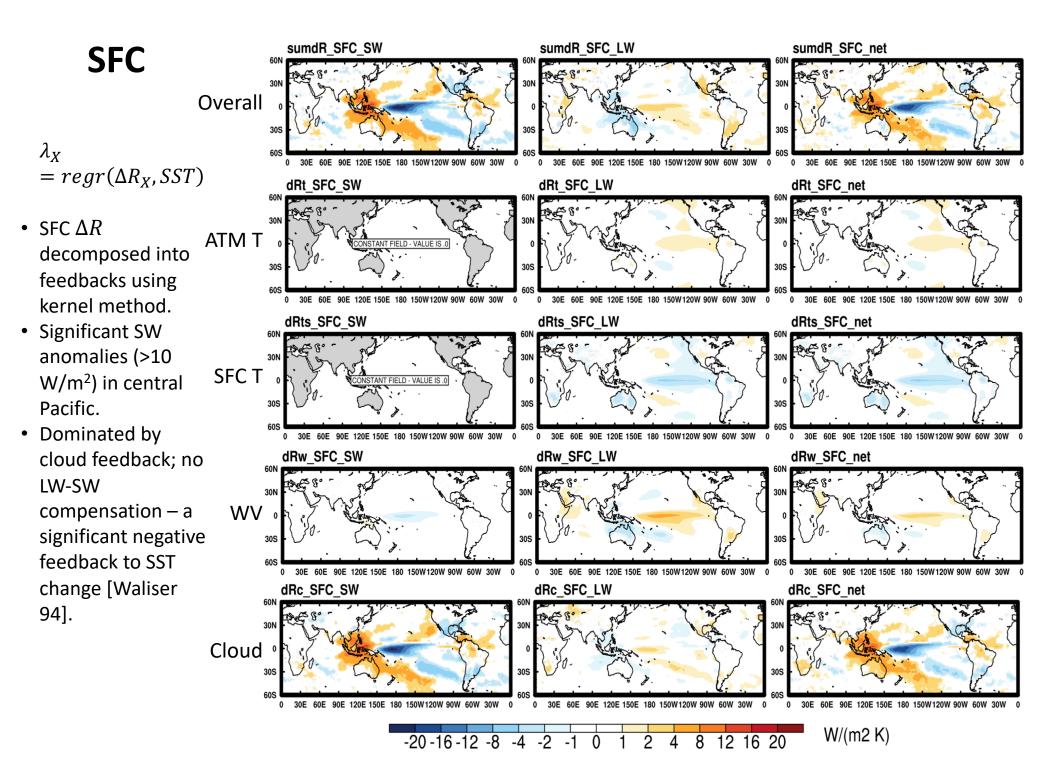
Overall

 λ_X $= regr(\Delta R_X, SST)$

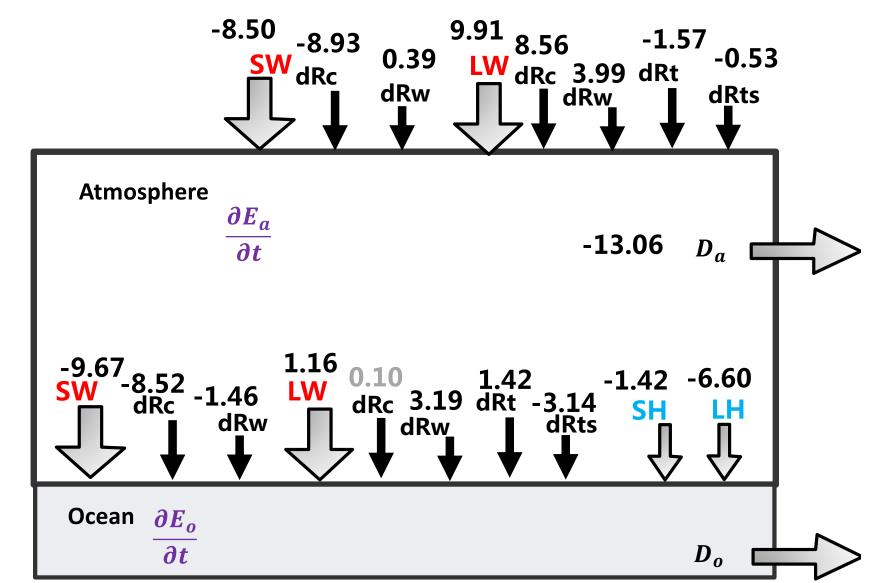
- ΤΟΑ ΔR decomposed into feedbacks using kernel method.
- Significant LW and SW anomalies (>10 W/m² regional) in ENSO.
- Dominated by cloud feedback, neutralized after LW-SW compensation (c.f. the debate).







The energy balance in Central Pacific (5N~5S, 180E~240E)



 $\lambda_X = regr(\Delta R_X, SST) [W/(m^2 K)]$

Radiative fluxes: CERES + Kernel decomposition

Non-radiative: ERAi

TOA:

SW(-) ~

LW(+)

• SFC SW_{cloud}(-) +

LH(-)

• ATM $LW_{cloud}(+)$ $\sim D_a(-)$

The energy balance in Central Pacific (5N~5S, 180E~240E)

• TOA: SW(-) ~ LW(+)

ATM

$$LW_{cloud}(+) \sim D_a(-)$$

• Cloud LW heating is the #1 energy source that drives the anomalous circulation (D_a)

Feedback	TOA	SFC	ATM		
SW	-8.50	-9.67	1.17		
dRc	-8.93	-8.52	-0.41		
dRw	0.39	-1.46	1.85		
LW	9.91	1.16	8.75		
dRc	8.56	0.10	8.46		
dRw	3.99	3.19	0.80		
dRt	-1.57	1.42	-2.99		
dRts	-0.53	-3.14	2.61		
SH		-1.42	1.42		
LH		-6.60	6.60		
netRad	1.42	-8.51	9.93		
Hori. Transp.			-13.06		

 $\lambda_X = regr(\Delta R_X, SST) [W/(m^2 K)]$

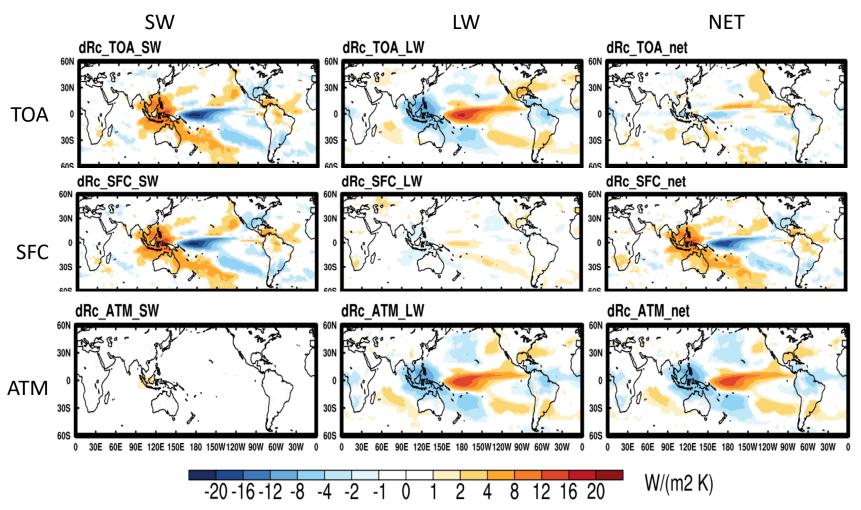
Radiative fluxes: CERES + Kernel decomposition

Non-radiative: ERAi

ATM

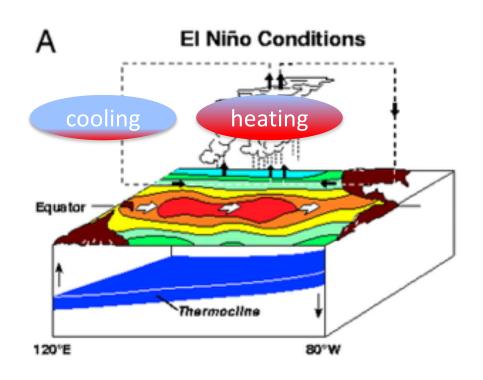
sumdR ATM SW sumdR ATM LW sumdR ATM net Overall λ_X $= regr(\Delta R_X, SST)$ dRt ATM SW dRt ATM LW dRt ATM net • ATM ΔR decomposed into ATM T feedbacks using kernel method. 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 0 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W Significant LW dRts ATM SW dRts ATM LW dRts ATM net anomalies (>10 W/m²) in central SFC T Pacific. Dominated by cloud feedback; no dRw ATM SW dRw ATM LW dRw ATM net LW-SW compensation – a significant negative WV feedback to SST change [Waliser 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 0 0 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 0 0 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 94]. dRc ATM SW dRc ATM LW dRc ATM net Cloud 0 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W 0 30E 60E 90E 120E 150E 180 150W120W 90W 60W 30W W/(m2 K)

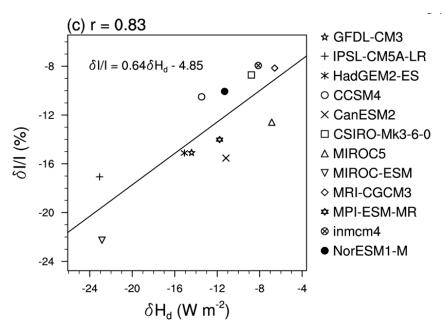
Cloud feedback



- Different perspectives to think of the neutralized TOA cloud (overall) radiative feedback in ENSO
 - SW-LW compensation
 - SFC-ATM compensation
- Implications
 - SFC SW: negative feedback [Waliser 94]
- ATM LW: positive feedback (via Bjerknes feedback: differential heating of cent. Pac. and warm pool => circulation and surface wind change => amplification of Δ SST) [Kolly&Huang 18]

Cloud feedback: differential heating





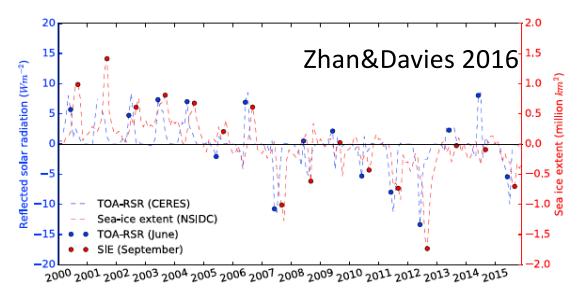
A strong correlation between change in tropical circulation strength and radiative differential heating is observed in CMIP5 models [Xia&Huang 2017]

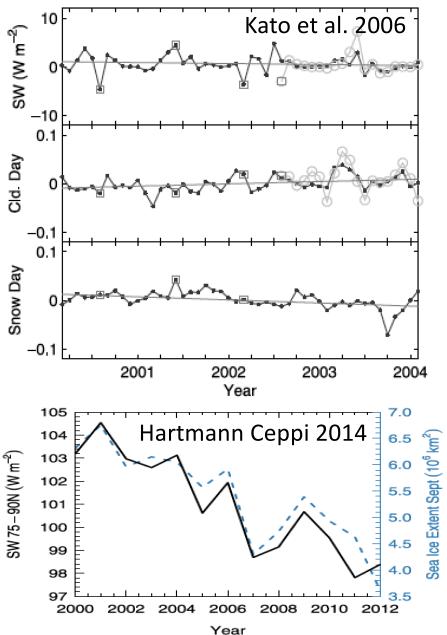
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ARCTIC SEA ICE AND RADIATION

Radiation questions in sea ice problem

- Is there a strong (negative) cloud feedback to SI change?
 - Early studies: yes [Kato 2006, etc.];
 - Longer record: no [Hartmann&Ceppi 2014, etc.]
- Does radiation predict SI?
 - June dR predicts September SIE [Choi et al. 2014; Zhan&Davies 2016]



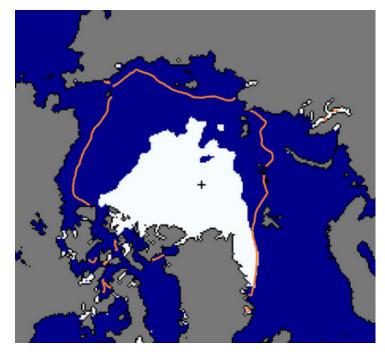


I have no answer ... But a caution

- Linear (e.g., Kernel) method for measuring ΔR_X Non-cloud: $\Delta R_X = K_X \cdot \Delta X$, $K_X = \frac{\partial R}{\partial X}$ Cloud: $\Delta R_C = \Delta R - \sum \Delta R_X$
- Issues: Linearity assumption
 - Cloud feedback: residual term
 - When ΔX is of large magnitude, $o(\Delta X^n)$ in Taylor expansion?
 - Coupling of different feedbacks, $o(\Delta X_1^m \Delta X_2^n)$?
- Solution?

Predict R-X relationship with a computationally efficient, non-linear model - Neural Network (NN) and then evaluate feedback according to definition [Zhu et al. 2019]:

$$\Delta R_X = R^{NN}(X + \Delta X) - R^{NN}(X)$$

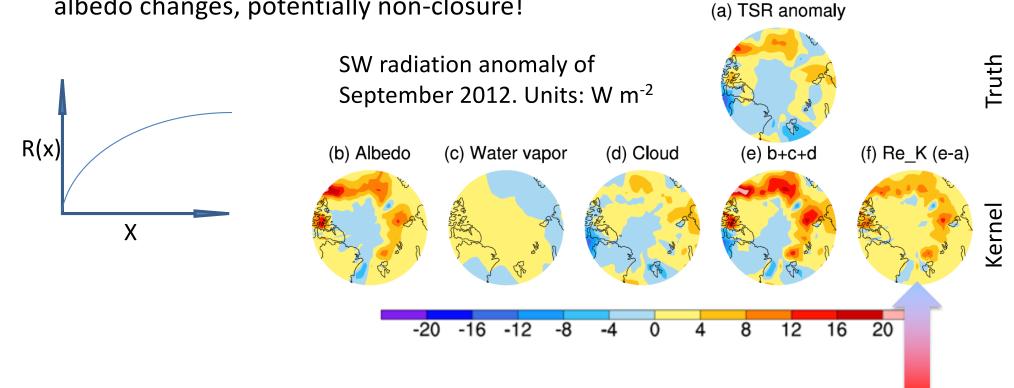


NSIDC Sea Ice Extent: Sep. 2012 Orange: 1979-2000 medium

 Arctic presents the largest climate and radiative perturbations.

Non-closure when large ΔR perturbation

• $\Delta R_X = K_X \cdot \Delta X$ Albedo kernel K_A is obtained by using small perturbation. If used to evaluated ΔR_A at large albedo changes, potentially non-closure!



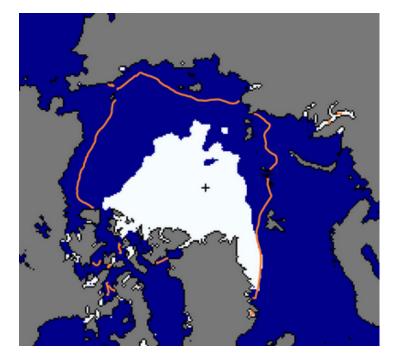
Noticeable non-closure in ΔR decomposition! [Zhu et al. 2019]

I have no answer ... But a caution

- Linear (e.g., Kernel) method for measuring ΔR_X Non-cloud: $\Delta R_X = K_X \cdot \Delta X$, $K_X = \frac{\partial R}{\partial X}$ Cloud: $\Delta R_C = \Delta R - \sum \Delta R_X$
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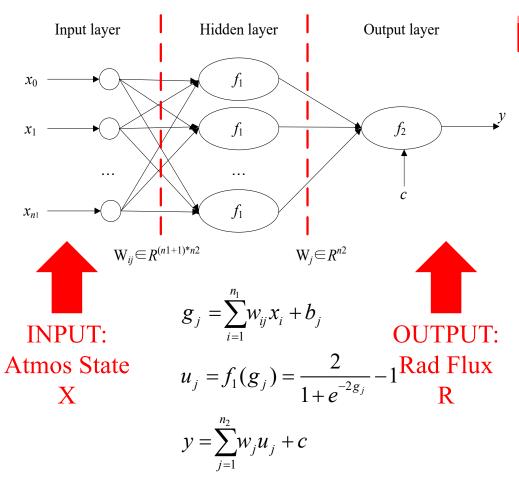
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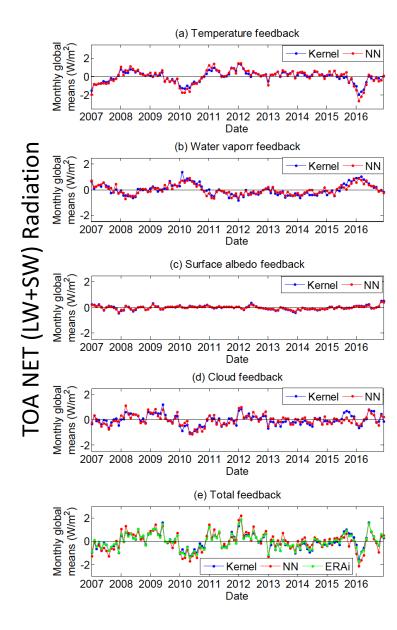
 Arctic presents the largest climate and radiative perturbations.

Neural Network Method



Outputs SSP AND N	et Incoming Shortwave R	adiation						
SSF /TSR	TCWV, SP, TCO3, FAL, TCIW, TCLW, HCC, MCC, LCC, Loc							
STRU	SK1, 110, 1200, 1500, 1CWV, Loc							
TOA Outgoing Longwave Radiation LCC, Loc								
ГТR	SKT, T10, T200, T500, Q200, Q500, Q700	, HCC, MCC, LCC, Loc						
Abbreviation	Description							
SSRC	Surface net solar radiation in clear sky, W	$/\mathrm{m}^2$						
SSR	Surface net solar radiation in all sky, W/m	2						
TSRC	Top net solar radiation in clear sky, W/m ²							
TSR	Top net solar radiation in all sky, W/m ²							
STRC	Surface net thermal radiation in clear sky, W/m ²							
STR	Surface net thermal radiation in all sky, W	$^{\prime}/\mathrm{m}^{2}$						
TTRC		Top net thermal radiation in clear sky, W/m ²						
TTR	Top net thermal radiation in all sky, W/m ²	2						
TCWV	Total column water vapor, kg/m ²							
SP	Surface pressure, Pa							
TCO3	Total column ozone, kg/m ²							
FAL	Forecast albedo, $(0,1)$	ERA interim						
TCIW	Total cloud ice water, kg/m ²							
TCLW	Total cloud liquid water, kg/m ²	dataset						
HCC	High cloud cover, $(0,1)$							
MCC	Medium cloud cover, $(0,1)$							
LCC	Low cloud cover, (0,1)							
Loc	Location, including longitude, sin(longitude	e) and cos(latitude)						
SKT	Skin temperature, K							
T10	Air temperature at 10 hPa level, K							
T200	Air temperature at 200 hPa level, K							
T500	Air temperature at 500 hPa level, K							
Q200	Specific humidity at 200 hPa level, kg/kg							
Q500	Specific humidity at 500 hPa level, kg/kg							
Q700	Specific humidity at 700 hPa level, kg/kg							

[Zhu et al. 2019]



Feedbacks: Kernel vs. NN

- Context: Interannual variation
- ΔR_X and ΔT time series: deseasoned and detrended; 2007-2016 (not used in training)
- NN very well reproduces the global mean overall feedback ΔR_{total} from the ERAi data and feedbacks ΔR_X analyzed from the kernel method.

Radiation -	В		RMSE			
	$\sum \triangle R_X^K$	$\sum \triangle R_X^{NN}$	$\triangle R^{NN}$	$\sum \triangle R_X^K$	$\sum \triangle R_X^{NN}$	$\triangle R^{NN}$
SSR	0.00	0.42	0.32	0.06	0.55	0.47
STR	0.00	-0.24	-0.23	0.15	0.29	0.27
TSR	0.00	0.39	0.27	0.05	0.49	0.41
TTR	0.00	-0.22	-0.03	0.12	0.31	0.17

[Zhu et al. 2019]

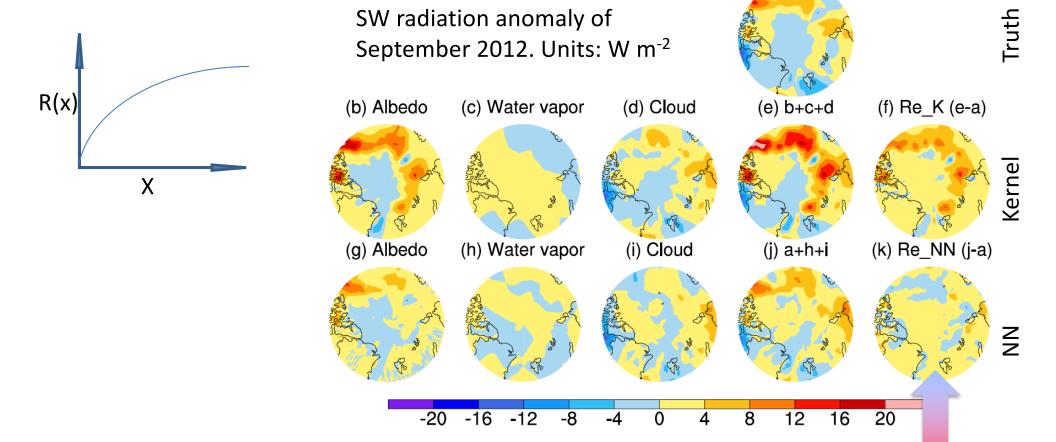
Nonlinearity in albedo feedback

(a) TSR anomaly

Better closure is achieved.

[Zhu et al. 2019]

• $\Delta R_X = K_X \cdot \Delta X$ Albedo kernel K_A is obtained by using small perturbation. If used to evaluated ΔR_A at large albedo changes, potentially non-closure!



Take home messages

- CERES and continued radiation measurements: essential for validating GCMs wrt ΔR closure.
- Cloud radiative feedback in ENSO is to cool Central Pacific (a <u>negative</u> feedback) at ocean surface but to warm the atmosphere above, which creates a differential heating between the Central Pacific and Warm Pool regions (a <u>positive</u> feedback).
- GCMs generally biased (too positive) wrt TOA cloud feedback in ENSO. The issue is more in radiative sensitivity $(\frac{\partial R}{\partial C})$ than cloud response (ΔC).
- Large climate perturbations, such as Arctic sea ice melts, create nonlinearity in radiative response, which requires nonlinear approaches for accurate feedback quantification.

References

- Kolly, A. and Y. Huang, (2018), The radiative feedback during the ENSO cycle: observations vs. models, J. Geophys. Res.-Atmos., https://doi.org/10.1029/2018JD028401
- Zhu, T., Y. Huang and H. Wei, (2019), Estimating climate feedbacks using a neural network, J. Geophys. Res.-Atmos. https://doi.org/10.1029/2018JD029223